Preliminary Schedule and Milestones (Revised July 3, 1996)
Southeast Pennsylvania Ozone Stakeholders

April 1,2	Organizational Meeting - Process Design Initial Scoping—Interests and Issues
May 6,7	Background Data Presentations
May 30,31	Data Presentations -Projected Emissions -Emission Controls -Modelling -Other States Developing Options
June 20,21	Refining Interests Developing Evaluation Criteria Emission Controls
July 8,9	Emissions 1990-2005 Emissions Control - Preliminary Target Options - Discussion and Evaluation
Aug 8,9	Vehicle Inspection and Maintenance Emissions Control - Continue Evaluation Select Packages of Emission Control for Model Run
Sept 19,20	Evaluation and Negotiation
Oct 3,4	Preliminary Decision Making
Nov 7,8	Drafting/Refining
Dec 12,13	Consensus

TECHNICAL PAPER

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Detecting and Tracking Changes in Ozone Air Quality

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This paper presents a statistical method for filtering out or moderating the influence of meteorological fluctuations on ozone concentrations. Use of this technique in examining trends in ambient ozone air quality is demonstrated with ozone data from a monitoring location in New Jersey. The results indicate that this method can detect changes in ozone air quality due to changes in emissions in the presence of meteorological fluctuations. This method can be useful in examining the effectiveness of regulatory initiatives in improving ozone air quality.

Introduction

It is well known that meteorology plays a significant role in establishing conditions conducive to the formation and buildup of high ozone concentrations.[1-3] Analysis of ozone air quality trends in the northeastern United States is hampered by the lack of a long-term quality-assured database, as well as by the variability in meteorology. Also, it is difficult to detect the change in ozone air quality due to the change in emissions in the presence of meteorological fluctuations.[4] Furthermore, unless the change in emissions is substantial, any improvement in ozone air quality achieved from modest emissions reductions can be easily masked by the variability in meteorology.[5]

Since ambient ozone concentrations are strongly influenced by meteorological fluctuations, statistically robust methods are needed to track the effectiveness of regulatory initiatives in improving ambient ozone air quality. We must separate different phenomena present in the time series of both meteorological and ozone data which have different characteristics such as long- and short-term variations. A precise examination of either meteorological or ozone data becomes extremely complex because both strongly affect each other and produce false effects for each side. Statistical methods currently being used[6-8] to detect ozone trends are not powerful enough to clearly separate random variations and meteorological effects from long-term trends.

In this paper, we present a method to filter out or moderate the influence of meteorology on ambient ozone levels, using surface temperature as a surrogate for all meteorological conditions that affect ozone. The results from the application of this method to ozone data from Cliffside Park, New Jersey, reveal a marked change in ambient ozone concentrations during the post-1988 period. This change in ozone concentrations in 1989 may be a result of controls on the volatility of fuel used in the Northeast.

Implications

Because the influence of stochastic and seasonal variations in meteorological conditions on ambient ozone concentrations is much greater than that of long-term changes in emissions of ozone precursors, it is difficult to assess the effectiveness of regulatory initiatives in improving ozone air quality. Although a meteorologically weighted measure of ozone may alleviate some of the difficulties associated with the analysis of ozone trends, a statistically robust method is necessary to detect changes in ozone air quality in the presence of meteorological fluctuations. This paper presents a technique for filtering out or moderating the influence of meteorology on ozone concentrations so that the impact of regulatory programs on ambient ozone air quality can be assessed.

Data and Analysis Procedures

Data

Hourly concentrations of ozone measured at the Cliffside Park monitor in northern New Jersey from 1983 through 1991 were obtained from the U.S. EPA's Aerometric Information Retrieval System (AIRS) database. Also, hourly values of surface temperature measured at LaGuardia Airport in New York City, which is the weather station nearest to the location of the ozone monitor, were assembled for the above time period. A subset of data consisting of daily maxima of temperature and ozone was derived from the hourly time series in the following analysis.

Method of Analysis

We assume that a time series of temperature or ozone may be represented as

$$X(t) = e(t) + S(t) + W(t) \qquad (1)$$

where X(t) is the original time series, e(t) is a trend component, S (t) is seasonal variation, and W(t) is white noise. In our analysis, we will separate the deterministic portions (e and S) from the short-term variations (white noise) in the data using the Kolmogorov-Zurbenko ($KZ_{m,p}$) filter.[9] The $KZ_{m,p}$ filter is a low-pass filter produced by repeated iterations of a simple moving average. The moving average (each iteration) is defined by

$$Y_i = \frac{1}{m}\sum_{j=-K}^{k} X_{i+j} \qquad (2)$$

where $m = 2k + 1$. The Y_i become the input for the second pass, and so on. Determination of the final low-pass filter (specifying "m" and the number of passes "p") is an iterative process in which the data user determines that the white noise has been removed.

The output time series, Y_t, is the low-frequency part of X_t,

$$Y_t = KZ_{m,p}\,(X_t). \qquad (3)$$

The Y_t contain both long-term trend and seasonal effects. The KZ filter and its statistical characteristics have been carefully studied by Zurbenko.[10]

When the $KZ_{29,3}$ [29-day length (m) with three iterations (p)] filter is applied to the daily maximum temperature and the log of daily maximum ozone concentration data, one obtains time series that exhibit no white noise (Figure 1). The filtered temperature and the log of ozone time series are denoted hereafter as $T_{kz}(t)$ and $O_{kz}(t)$, respectively.

Quantile-quantile (QQ) plots of the residual of the filtered temperature $[T(t) - T_{kz}(t)]$ and the log of ozone $[\{O(t) - O_{kz}(t)\} = W(t)]$ are presented in Figures 2(a) and 2(b), respectively, to illustrate that they are indeed white noise; a QQ plot of 3,000 normal random numbers is shown in Figure 2(c) for comparison. Periodograms (not shown here) of the residuals also confirm that they are almost white noise. In addition, a scatter plot of ozone residuals and temperature residuals indicates no relationship between them (Figure 3). Therefore, we proceed with our analysis of noise-free (filtered) temperature and ozone data.

A linear regression of the filtered log of ozone concentrations $[O_{kz}(t)]$ on filtered temperature $[T_{kz}(t)]$ data was performed:

$$O_{kz}(t) = aT_{kz}(t) + b + \varepsilon(t) \qquad R^2 = 0.83 \tag{4}$$

where a and b are fitted parameters, $\varepsilon(t)$ are the residuals of the relationship, and R^2 is the square of the correlation coefficient.

The averaged annual profiles of temperature and ozone, presented in Figure 4, indicate a phase lag between temperature and ozone. Ozone concentrations are influenced by both emissions and meteorological variables, whereas temperature is dictated primarily by the prevailing meteorological conditions. The linear relationship between $O_{kz}(t)$ and $T_{kz}(t)$ becomes stronger when the temperature data are lagged by 19 days (Figure 5).

$$O_{kz}(t) = aT_{kz}(t+19) + b + \varepsilon(t) \qquad R^2 = 0.93 \tag{5}$$

The $\varepsilon(t)$ reveal changes in ozone attributable to changes in emissions. Moreover, the relationship is devoid of the white noise that would characterize a regression approach using the raw data. A $KZ_{1\,year,3}$ filter was applied to $\varepsilon(t)$,

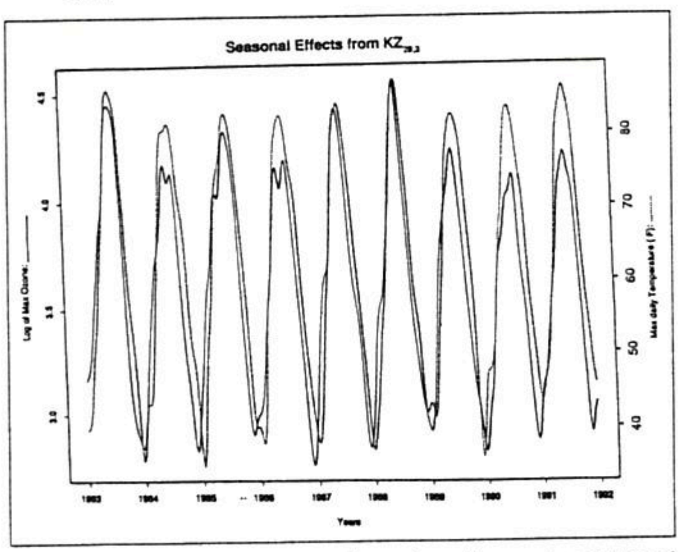

Figure 1. Seasonal variation in the daily maxima of temperature and log of ozone derived from the application of $KZ_{29,3}$ to the original time series.

$$\varepsilon(t) = \varepsilon_{KZ_{1\,year,3}}(t) + \delta(t) \tag{6}$$

and $\varepsilon(t)$ reveal a change in ozone concentrations in 1989 that cannot be attributed to temperature fluctuations (Figure 6). It should be noted that the ordinate in Figure 6 corresponds approximately to percent changes from the long-term mean. Thus, this

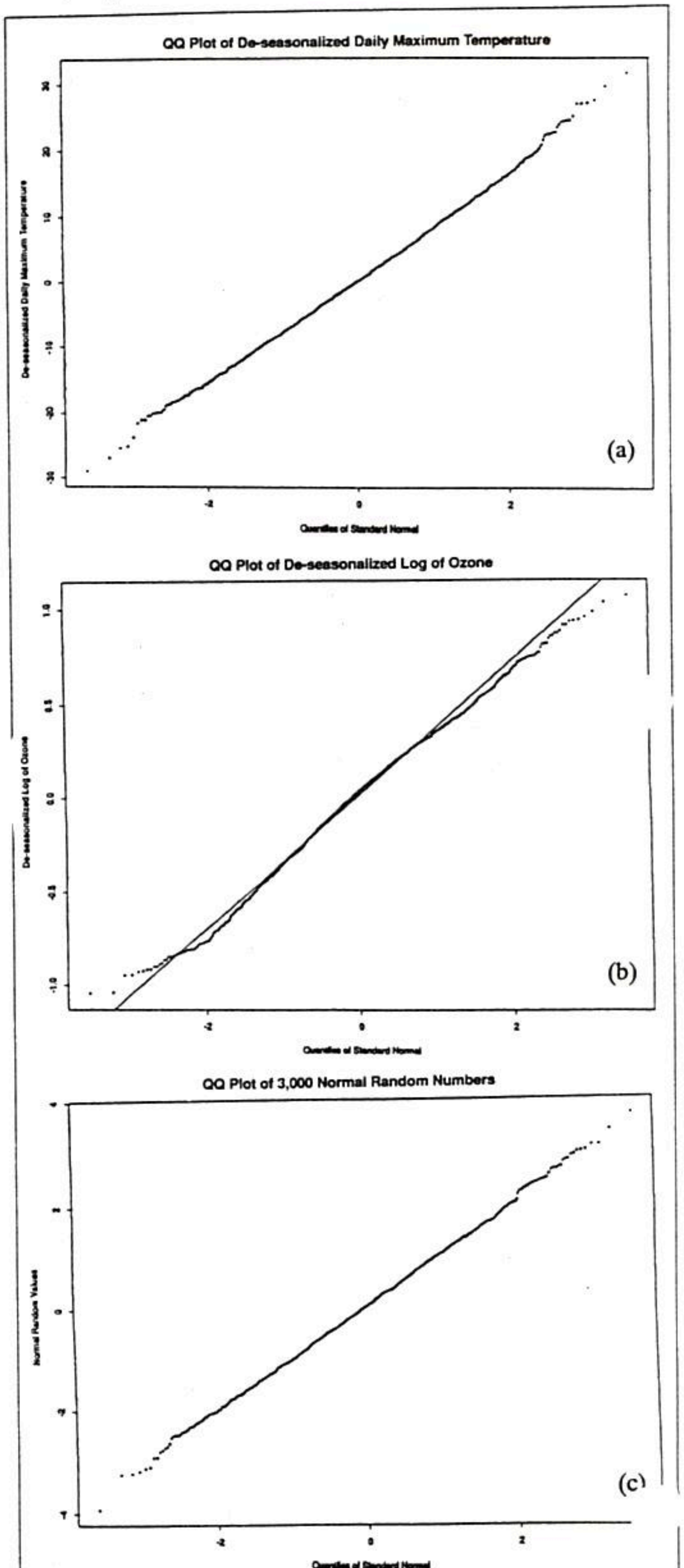

Figure 2. (a) Quantile-quantile plot of de-seasonalized daily maxima of temperature. (b) Same as (a), except for the log of ozone daily maxima. (c) Same as (a), except for 3,000 normal random numbers.

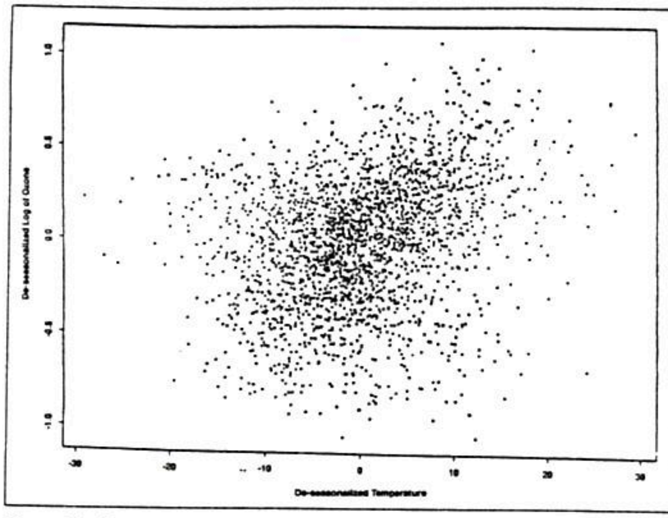

Figure 3. Scatter diagram between de-seasonalized daily maxima of temperature and log of ozone.

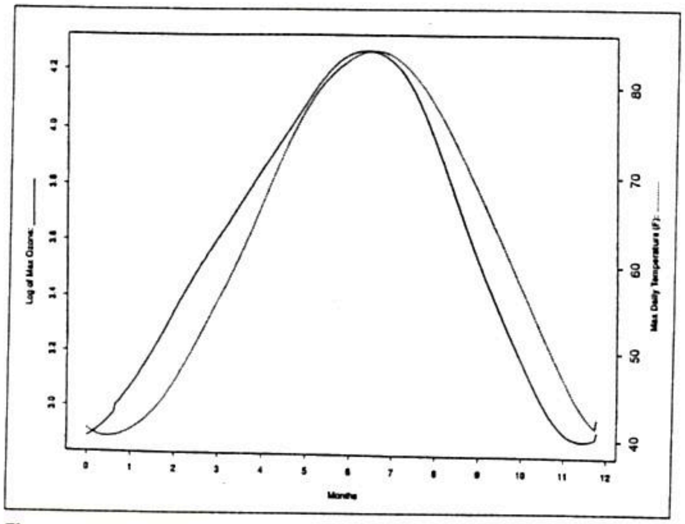

Figure 4. Averaged annual profiles of temperature and ozone.

procedure reveals changes in ozone concentrations which may be attributable to changes in emissions.

The original ozone time series, O(t), now may be defined as temperature-dependent time series, $O_{kz}(t)$, and the white noise process, W(t),

$$O(t) = W(t) + O_{kz}(t). \qquad (7)$$

For the data set examined here, W_t and $O_{kz}(t)$ contribute approximately 20 and 80 percent, respectively, to the total variance in O(t). Substituting expressions (5) and (6) into expression (7), the ozone time series then is represented as

$$O_t = W_t + [aT_{kz}(t + 19) + b] + \varepsilon_{KZ_{1\,year,3}}(t) + \delta(t). \qquad (8)$$

In the right side of expression (8), the first term represents short-term turbulence which is always uncorrelated with long-term effects. The second term represents long-term and seasonal temperature effects in ozone, and the third term reflects long-term emissions effects unexplained by temperature. The fourth term, $[\delta(t) = \{\varepsilon(t) - \varepsilon_{KZ_{1\,year,3}}(t)\}]$, represents small ozone seasonal variations induced by meteorological variables other than temperature. With the regression equation (5) explaining 93 percent of the variance in $O_{kz}(t)$, the contribution of the seasonal component, $T_{kz}(t+19)$, to the total variance in O(t) is approximately 70 percent (0.93 x 0.80).

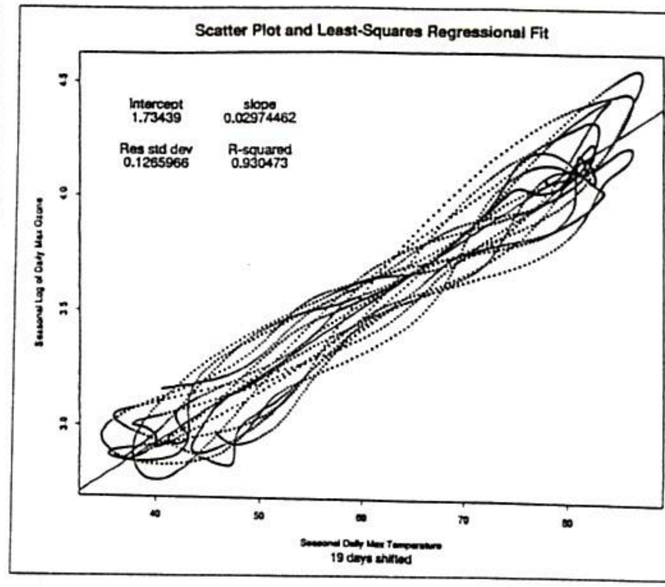

Figure 5. Linear least-squares regression fit for the seasonal components of temperature and log of ozone daily maxima.

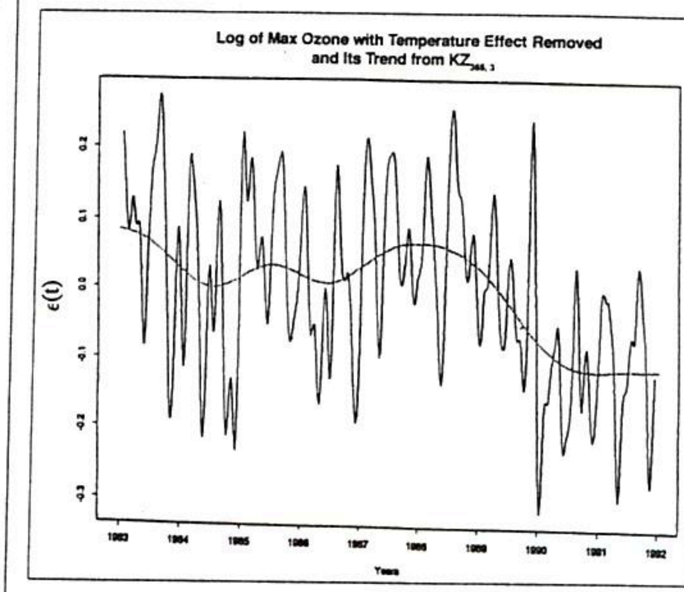

Figure 6. The variation in log of ozone maxima when the temperature effect is removed from ozone concentrations [ε(t) in expression (5)] along with the trend derived from the application of $KZ_{1\,year,3}$ to ε(t).

Expressions (4) and (7) are given for the natural logarithm of the original ozone data. An additive term ε(t) then has a multiplicative effect, exp{ε(t)}, in the original data. Since ε(t) is sufficiently small, we have

$$\exp\varepsilon(t) \simeq 1 + \varepsilon(t);\ \text{i.e., } \ln(1 + \varepsilon(t)) \simeq \varepsilon(t). \qquad (9)$$

Hence, ε(t)*100 or δ(t)*100 in Figure 6 corresponds to percent changes in long-term emissions effects in the original ozone data. The zero level of ε(t) corresponds to the mean value of the total ozone data used for analyses. As a first step in our analysis, a log-transform of the original data was performed to stabilize the variance of noise W(t) in expression (7), which also has a multiplicative effect on the ozone concentrations (ppb).

Results and Discussion

The presence of significant short-term variations and strong seasonality in temperature and ozone data make it difficult to draw inferences using traditional statistical methods. For example, a plot of annual average ozone concentrations does not reveal a trend during the period 1983 through 1991. Similarly, a scatter plot of daily maxima of temperature versus ozone showed little relationship between these two variables. Our analysis of ozone data at Cliffside Park, New Jersey, reveals that the long-term and seasonal variations in the original time series account for approximately 10 and 70 percent, respectively, of the total variance in the original time series. The stochastic component (white noise) is approximately 20 percent of the total variance in the original time series data. Traditional statistical methods cannot perform well under conditions in which the effect that we want to discern is much smaller than that of the seasonal and stochastic components in the data. The primary advantage of the KZ filter is that it can separate short- and long-term variations in time series of meteorological and air quality data because of its very high frequency resolution characteristics.

The strong relationship between $KZ_{29,3}(T_{t+19})$ and $KZ_{29,3}(O_t)$ indicates a significant linear component of the effect of temperature on ozone concentrations. This effect is absent from the time series of the residuals [$\varepsilon(t)$] in expression (5) above. We have also applied this method to daily maxima of temperature and ozone for the ozone season only (i.e., April 15 to October 15), treating the data in the October 16 to April 14 period as missing data. As expected, analysis of data covering only the ozone season also has indicated a similar change in ozone levels during 1989. We also have applied this method to ozone data at another nearby monitoring location and found the results similar to those obtained at the Cliffside Park monitoring location.

Since the influence of meteorology on ambient ozone levels has been moderated in this study, the change in ozone levels detected in 1989 might be attributable to changes in emissions due to regulatory actions, such as the fuel volatility control strategy implemented by the Northeast states in 1989.[11] However, it is important to investigate whether other limiting factors, such as NO_x availability, may have also contributed to the change in ozone levels in the post-1988 period. Furthermore, it is plausible that other meteorological variables, such as ventilation, water vapor, isolation, etc., may have also influenced ozone concentrations. Such effects are evidenced by the semi-annual cycle present in the temperature-independent ozone time series in Figure 6. If data are available, the influence of the above meteorological variables on ozone concentrations also may be removed similarly by this method. We currently are applying this technique to data spanning the period 1980 through 1992 from several monitoring stations, in an effort to demonstrate the method's robustness and to examine trends in ozone air quality in the northeastern United States. These results, when combined with trends in ozone precursor concentrations, should enable us to relate changes in ambient ozone air quality to changes in emissions and thus track progress toward ozone compliance.

Summary

In this paper, we presented a technique to detect changes in ozone air quality in the presence of meteorological fluctuations. The results indicate that the method can filter out or moderate the influence of meteorology on ozone, enabling us to track changes in ozone air quality due to changes in emissions. This then will allow us to evaluate the effectiveness of regulatory programs in improving ambient ozone air quality.

Acknowledgments

The authors gratefully acknowledge the support of Drs. Robert Eskridge and Thomas Karl of the Global Climate Laboratory, National Climatic Data Center, Asheville, North Carolina, for the development of the moving average filter used in this study, under NOAA Contract 50EANE2000078. One of the authors (I.Z.) would like to acknowledge NIEHS Grant P42 ES04913-04 for partial support of the development of the filtering procedur[illegible]e [illegible] authors also would like to thank professors Steven Porter [illegible]e University of Idaho and Peter Bloomfield of North Carolina State University for their critical review and constructive comments on the manuscript, and Mr. Shiqun Li for his assistance with the data analysis.

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About the Authors

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Implications

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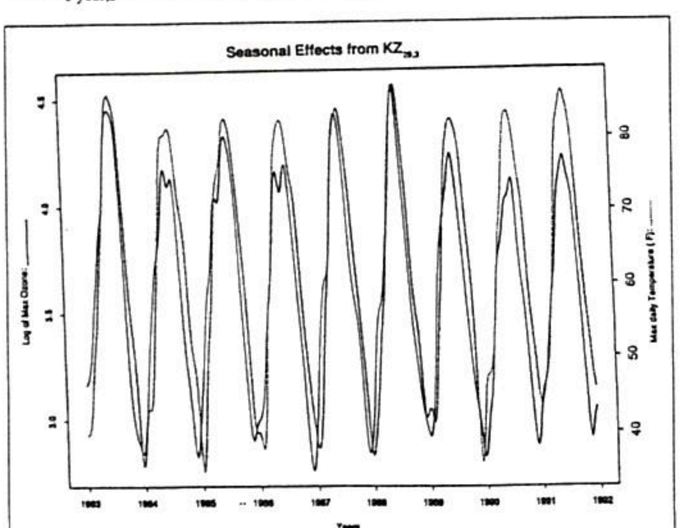

Figure 1. Seasonal variation in the daily maxima of temperature and log of ozone derived from the application of $KZ_{29.3}$ to the original time series.

$$\varepsilon(t) = \varepsilon_{KZ_{1\ year,3}}(t) + \delta(t) \tag{6}$$

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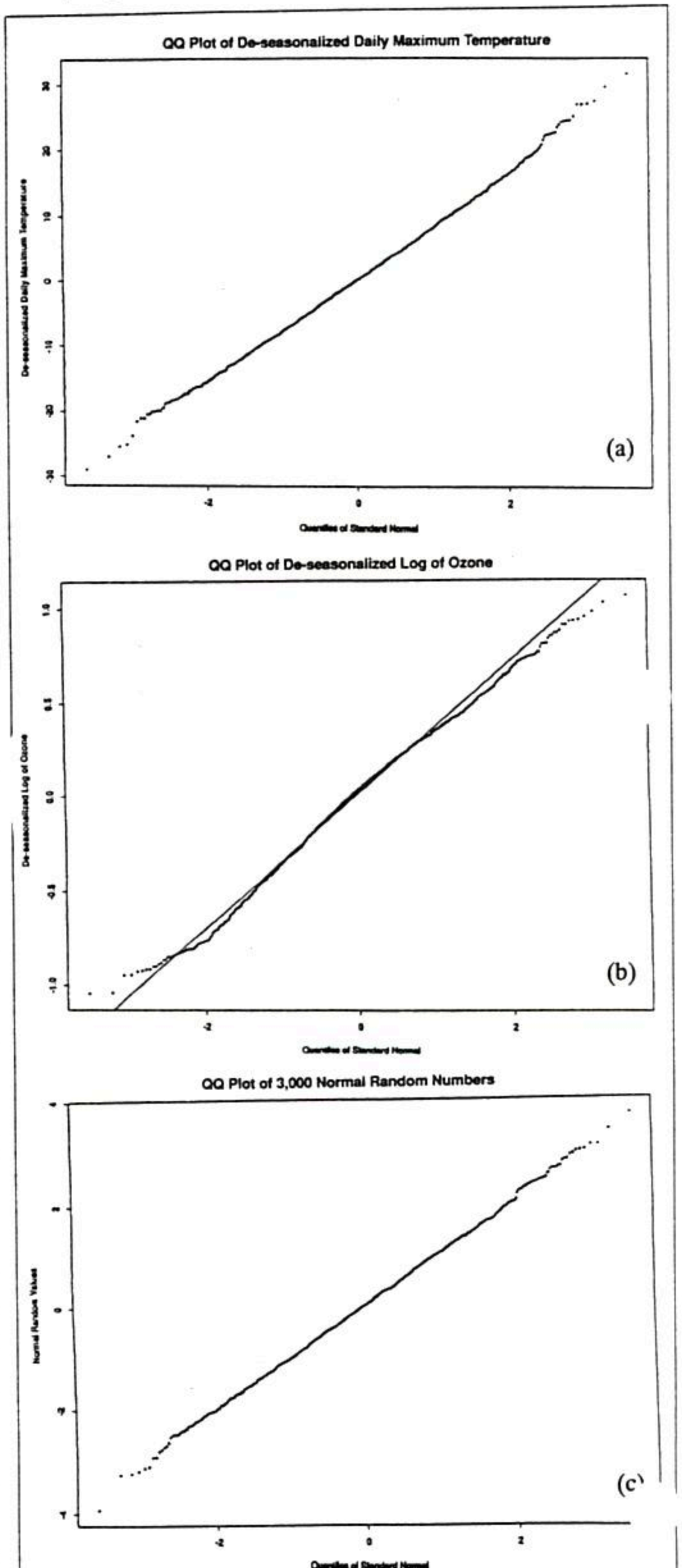

Figure 2. (a) Quantile-quantile plot of de-seasonalized daily maxima of temperature. (b) Same as (a), except for the log of ozone daily maxima. (c) Same as (a), except for 3,000 normal random numbers.

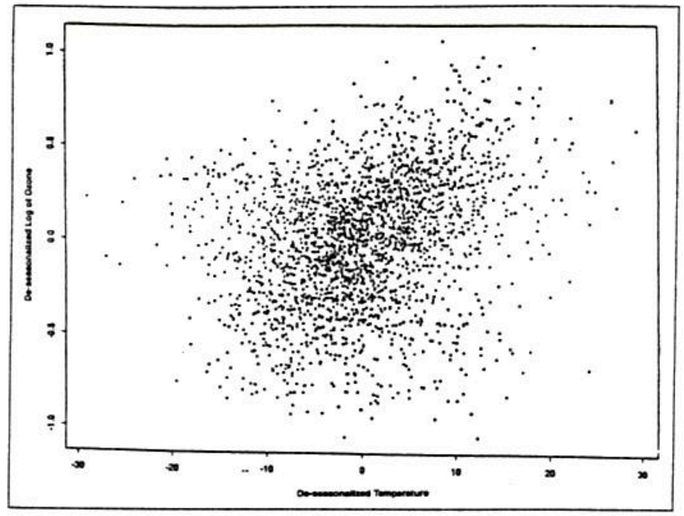

Figure 3. Scatter diagram between de-seasonalized daily maxima of temperature and log of ozone.

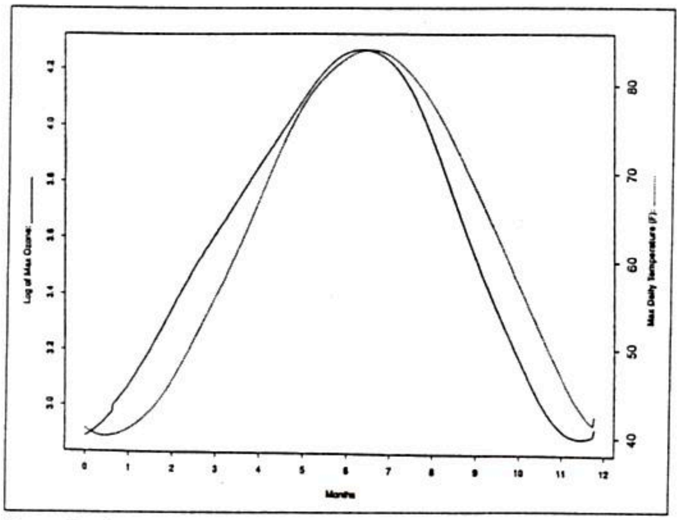

Figure 4. Averaged annual profiles of temperature and ozone.

procedure reveals changes in ozone concentrations which may be attributable to changes in emissions.

The original ozone time series, O(t), now may be defined as temperature-dependent time series, $O_{kz}(t)$, and the white noise process, W(t),

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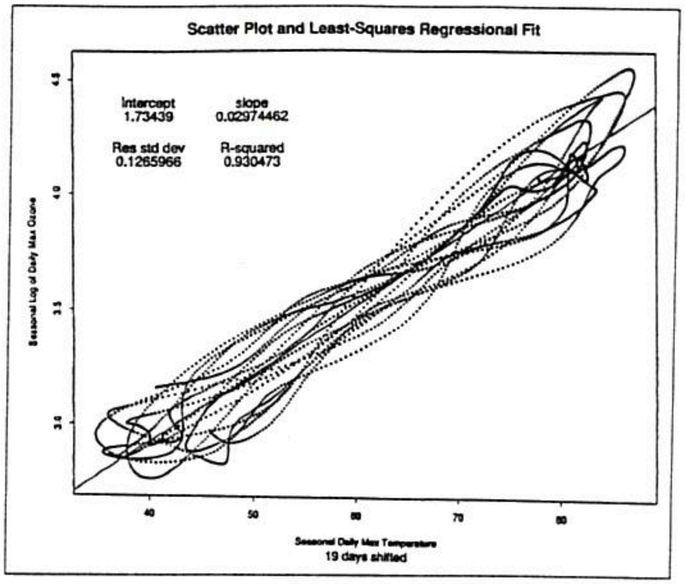

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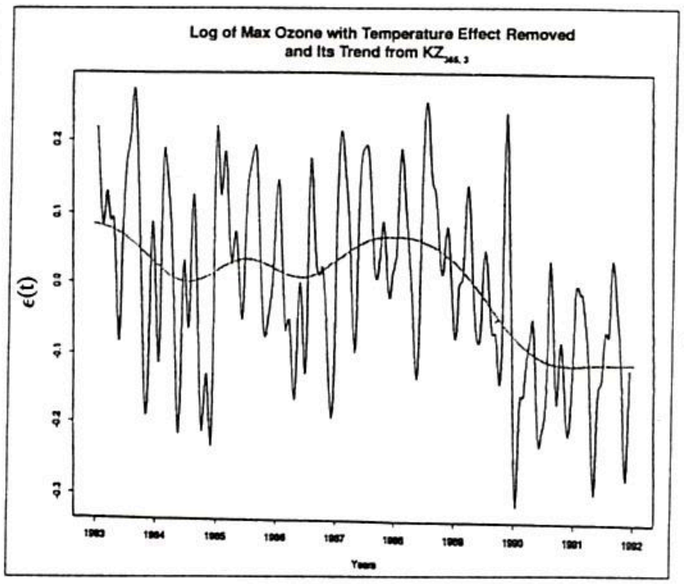

Figure 6. The variation in log of ozone maxima when the temperature effect is removed from ozone concentrations [ε(t) in expression (5)] along with the trend derived from the application of $KZ_{1\,year,3}$ to ε(t).

Expressions (4) and (7) are given for the natural logarithm of the original ozone data. An additive term ε(t) then has a multiplicative effect, exp{ε(t)}, in the original data. Since ε(t) is sufficiently small, we have

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Hence, ε(t)*100 or δ(t)*100 in Figure 6 corresponds to percent changes in long-term emissions effects in the original ozone data. The zero level of ε(t) corresponds to the mean value of the total ozone data used for analyses. As a first step in our analysis, a log-transform of the original data was performed to stabilize the variance of noise W(t) in expression (7), which also has a multiplicative effect on the ozone concentrations (ppb).

Results and Discussion

The presence of significant short-term variations and strong seasonality in temperature and ozone data make it difficult to draw inferences using traditional statistical methods. For example, a plot of annual average ozone concentrations does not reveal a trend during the period 1983 through 1991. Similarly, a scatter plot of daily maxima of temperature versus ozone showed little relationship between these two variables. Our analysis of ozone data at Cliffside Park, New Jersey, reveals that the long-term and seasonal variations in the original time series account for approximately 10 and 70 percent, respectively, of the total variance in the original time series. The stochastic component (white noise) is approximately 20 percent of the total variance in the original time series data. Traditional statistical methods cannot perform well under conditions in which the effect that we want to discern is much smaller than that of the seasonal and stochastic components in the data. The primary advantage of the KZ filter is that it can separate short- and long-term variations in time series of meteorological and air quality data because of its very high frequency resolution characteristics.

The strong relationship between $KZ_{29,3}(T_{t+19})$ and $KZ_{29,3}(O_t)$ indicates a significant linear component of the effect of temperature on ozone concentrations. This effect is absent from the time series of the residuals $[\varepsilon(t)]$ in expression (5) above. We have also applied this method to daily maxima of temperature and ozone for the ozone season only (i.e., April 15 to October 15), treating the data in the October 16 to April 14 period as missing data. As expected, analysis of data covering only the ozone season also has indicated a similar change in ozone levels during 1989. We also have applied this method to ozone data at another nearby monitoring location and found the results similar to those obtained at the Cliffside Park monitoring location.

Since the influence of meteorology on ambient ozone levels has been moderated in this study, the change in ozone levels detected in 1989 might be attributable to changes in emissions due to regulatory actions, such as the fuel volatility control strategy implemented by the Northeast states in 1989.[11] However, it is important to investigate whether other limiting factors, such as NO_x availability, may have also contributed to the change in ozone levels in the post-1988 period. Furthermore, it is plausible that other meteorological variables, such as ventilation, water vapor, isolation, etc., may have also influenced ozone concentrations. Such effects are evidenced by the semi-annual cycle present in the temperature-independent ozone time series in Figure 6. If data are available, the influence of the above meteorological variables on ozone concentrations also may be removed similarly by this method. We currently are applying this technique to data spanning the period 1980 through 1992 from several monitoring stations, in an effort to demonstrate the method's robustness and to examine trends in ozone air quality in the northeastern United States. These results, when combined with trends in ozone precursor concentrations, should enable us to relate changes in ambient ozone air quality to changes in emissions and thus track progress toward ozone compliance.

Summary

In this paper, we presented a technique to detect changes in ozone air quality in the presence of meteorological fluctuations. The results indicate that the method can filter out or moderate the influence of meteorology on ozone, enabling us to track changes in ozone air quality due to changes in emissions. This then will allow us to evaluate the effectiveness of regulatory programs in improving ambient ozone air quality.

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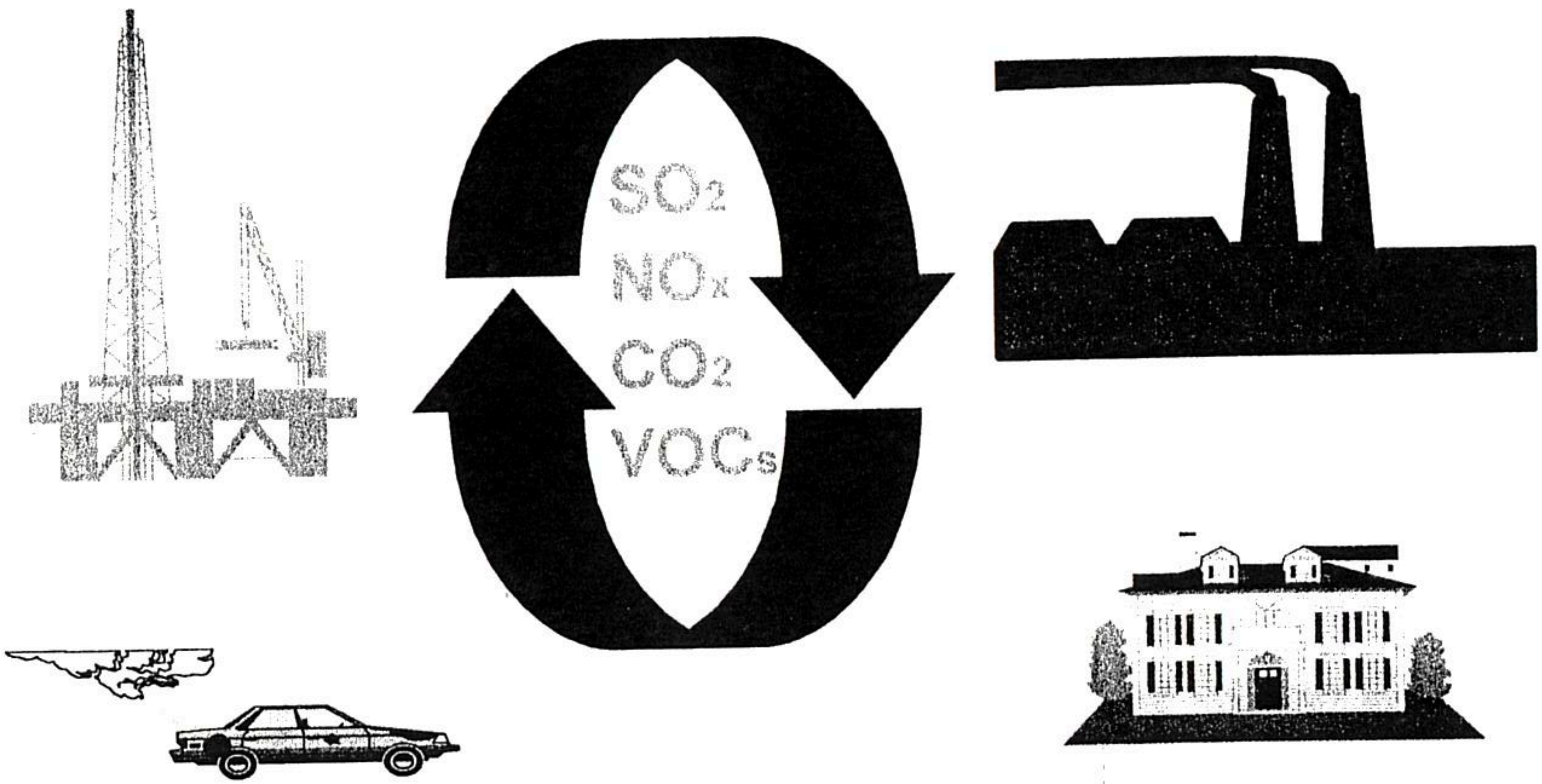
OPPORTUNITIES TO IMPROVE AIR QUALITY MANAGEMENT

EDF

STRATEGIC VISION



EDF

TRADING POLICY ASSETS

- ☆ More Environmental Bang for the Buck
- ☆ Highly Effective if Monitoring and Enforcement are Adequate
- ☆ Rewards Innovation and Stimulates R&D
- ☆ Creates an Environmental Asset which can aid in Financing Pollution Control

EDF

EMISSIONS-BASED POLICY ASSETS

- Caps on Real Emissions
- Absolute Accountability for Sources' Emissions Reduction Performance
- Seals the Door to the Bureaucratic Back-Room
- Transforms "Regulatory Reform","Reinventing Government" and "Flexibility" into Environmental Allies

KEY POLICY ELEMENTS

- Seasonal Limits On Actual Emissions
- Required Reductions From Those Limits
- Banking Of Emission Trading Units
- Minimize Transaction Constraints
- Intersector And Interpollutant Trading Regional Emissions Trading

BASIC DIFFERENCES BETWEEN C&C AND ERMS

<u>Command & Control</u>	<u>ERMS</u>
We tell you what you will do.	*You* tell us what you will do.
We tell you which units to control.	*You* pick which units to control.
We tell you the required reduction/control options per emission unit.	We tell you the overall reduction to be achieved, *you* pick the units to control.

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ADVANTAGES OF A REGIONAL POLICY

- Improved Fit Between the Problem and Strategy
- Improved Prospects for Solving the Problem
- Reduced Cost
- Improve Potential for Success of a Market
- Removes any Economic Distortion Between States

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BUILDING THE MARKET

☆ SUPPLY

- MERCs
- Stationary Sources
- LEVs
- Repair
- In-use Reductions
- Alternative Fuels

☆ DEMAND

- Emissions Caps
- Flexibile Compliance
- Nonattainment Trading
- Economic Incentive Program

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WHY WE SELECTED ERMS

- Allows Additional Flexibility
- Allows The Marketplace To Determine Where Reductions Come From
- Introduces A Profit Motive
- We Did Not Know Where To Go For Command & Control

WHAT IS ERMS?

- A system to obtain additional reduction from point sources
- CAA requires +/- 3% overall reductions in VOM per year
- Point sources will give their share each year
- Program switches to maintenance when attainment reached
- Other programs will be implemented to control mobile and area sources

WHAT IS ERMS?

A SYSTEM THAT ALLOWS A SOURCE TO

- REDUCE THEIR OWN EMISSIONS
- BUY SOMEONE ELSE'S EMISSION REDUCTIONS
- GET SOMETHING IN RETURN FOR OVER-COMPLIANCE

WHY WE PICKED ERMS

- CHICAGO AREA WILL NOT REACH ATTAINMENT BY USE OF CURRENTPLAN 15% RFP

- ADDITIONAL REDUCTIONS NEEDED FROM ALL SOURCES

  POINT AREA MOBILE
  IN ABOUT EQUAL PORTIONS FROM EACH SECTOR

- COMPLIANCE COST SAVINGS FOR AREA

POINT SOURCE REDUCTIONS ARE REQUIRED BECAUSE

- Driven by CAA and RFP provisions

CHOICE WAS...

- Continue selected command and control
- Across the board reductions
- *New options* - **ERMS**

OPERATIONAL COMPONENTS OF ERMS

- Seasonal control program: May 1 - Sept. 30
- A baseline must be established as a benchmark:

  Based On Facility-Wide VOM Emissions

  Must Use Actual Seasonal VOM Emissions

  Average Of 2 Out Of Last 3 Years (1994-1996)

  Some Emission Units Are Excluded From Baseline

  Some Adjustments Are Made To Baseline

- Seasonal emissions recordkeeping & reporting are required

- Seasonal emissions for each year must be less than Allotted ATUs for that year, otherwise ATUs must be sought from market

- Emissions recordkeeping & reporting coordinated with AERs

- Allotments and baseline incorporated into CAAPP permit